Individual wage growth: the effects of industry experience and firm tenure

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Abstract

This paper estimates the wage and mobility effects of experience in an industry. It uses a simultaneous equation model that accounts for the potential endogeneity of job tenure and industry experience in the wage determination process and allows for nonlinearities in the effects of interest. The empirical model is estimated using a large panel of Italian workers for the years 1986-2004. Results show that wage returns to industry experience are much higher than wage returns to job seniority. The hypotheses of exogeneity of job seniority and industry experience can be tested and are rejected.

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1 Introduction

There is solid evidence that a worker earns much higher wages as tenure in her firm and in her industry[1] rises. This would suggest that mobility in the labour market has large wage penalties. Yet there is also extensive evidence showing that workers who earn high wages are typically very mobile. This *prima facie* contradicting result suggests that estimating returns to firm tenure is not a straightforward exercise and that treating all job-to-job transitions equivalently may be misleading. Yet measuring the effect of tenure and experience is of great importance: quantifying the role of firm tenure and industry experience for wage growth is critical for researchers and policy makers alike. For researchers it sheds light on the role of different types of human capital for mobility and wages and on the wage returns of different mobility levels. For policy-makers knowing the "rewards" of tenure and industry experience is valuable for labour market mobility, contracts and compensation policies. If, for example, industry experience is found to be important for wage growth then public policy might consider specific interventions for displaced workers employed in a shrinking sector as opposed to displaced workers in a booming sector.

This paper offers new evidence of the wage returns to industry experience by developing and estimating a model where wages, industry experience and job duration are simultaneously determined. I estimate this model using data for a large sample of Italian male and female workers from the *Worker Histories Italian Panel* for 1985-2004. This paper offers the first estimate of the returns to industry experience using Italian panel data. To the best of my knowledge it is also the first simultaneous estimation of wage growth, firm tenure and industry experience. The model allows me to estimate the effects of labour market experience, industry experience and firm tenure on wages and mobility and accounts for the possible cross-equation correlation of individual and match heterogeneity. The main results show that wage returns to industry experience are much higher than wage returns to job

[1] "Industry" and "sector" are used interchangeably.

seniority, so that on average mobility across sectors is associated with a higher short-term wage penalty than mobility within the same economic sector. For males, returns to industry tenure are around four times higher than returns to job seniority for the first years on the job. Returns to labour market experience are four percent per year for the first five years. Results for females are qualitatively similar but show lower returns to labour-market experience and higher returns to industry experience and firm seniority. There is also evidence that wages and employment duration are simultaneously determined: individuals with "better" unobservables (unobservable characteristics that are associated with conditionally higher wages) stay on the job longer, and "good" matches (that have conditionally higher wages) are less likely to be destroyed. The hypotheses of no simultaneity of seniority and industry experience across equations are easily rejected.

The concern that firm tenure may be endogenous in the wage equation, i.e. the possibility of unobservables affecting both wages and employment duration, has been considered since Abraham and Farber (1987). They find positive returns to seniority to be an artifact of sample selection in the sense that "workers in longer jobs earn more throughout" (Abraham and Farber 1987, page 278). As a consequence, a simple Ordinary Least Squares (OLS) regression of wages on tenure will not yield credibly unbiased estimates. Altonji and Shakotko (1987) propose an Instrumental Variable (IV) technique to account for this endogeneity that has influenced a number of related papers [2].

Neal (1995) and Parent (2000) argue that industry experience might also be an important determinant of wage growth. Both papers find that industry tenure is a key determinant of wages. Neal (1995) uses a survey of displaced workers for which industry experience can be taken as exogenous at the time of displacement. More recently Dustmann and Meghir

[2] Among many others, Topel (1991) offers related evidence of the importance of firm-specific human capital while using longitudinal datasets to account for the endogeneity problem discussed above. They find that lower bounds for wage returns of firm seniority are around 2.5 percent a year on average. Topel and Ward (1992) on the other hand stress the importance of job mobility as a source of wage growth for young American males.

(2005) employ a similar strategy to study the wage impacts of different sources of human capital using data from Germany. They find that returns to sector tenure are positive for skilled workers, but are not significantly different from zero for unskilled workers. Studies using displaced workers provide interesting and useful results but do suffer from issues of external validity since a sample of displaced workers is unlikely to be representative of the labour market as a whole.

Parent (2000) on the other hand uses the same IV technique as Altonji and Shakotko (1987) to investigate the role of industry experience on wages. More recently Sullivan (2010) and Williams (2009) use similar techniques, and both find industry-specific human capital to be an important determinant of wage growth. Lillard (1999) argues that finding an instrument that is both exogenous and sufficiently strong is not credible, and that IV estimations such as Altonji and Shakotko (1987) can be criticised on the ground of instrument validity. Lillard (1999) uses U.S. data to estimate a simultaneous model with a wage equation and an job duration equation. He finds evidence suggesting that tenure might be endogenous in the wage equation, and that this endogeneity might be driven by unobservables. Dostie (2005) uses French data and finds that wages and job tenure are simultaneously determined. Both Lillard (1999) and Dostie (2005) focus on the returns to firm tenure and do not include industry experience in their analysis. This paper develops a three-equation model that builds upon Lillard (1999) for estimation strategy and identification, while focusing primarily on wage and mobility effects of industry experience.

2 Estimating returns to experience and seniority

The model below estimates wage and mobility effects of job tenure industry experience, labour market experience and job tenure[3]. Describing an ideal thought experiment can be

[3]For a comprehensive discussion on how to treat unobserved worker, firm, and match heterogeneity in a model of wage differentials see Woodcock (2008).

instructive for understanding the empirical challenges that arise from such an estimation. Let us imagine that in each time period workers are randomly assigned to jobs, which end at an random moment in the future. In this case a simple OLS regression of wage on experience, industry-experience and seniority would unveil their causal effect on wages.

Real-world labour markets do not work like our thought experiment, however. Both sides of the market are actively seeking their best opportunities (as in Jovanovic 1979): workers do not choose their job randomly and firms do not hire workers randomly. Over time, the set of jobs that survives may be self-selected. Workers that have longer job spells may be systematically different from workers that do not, and jobs that last longer may be systematically different from jobs that do not. For example, workers might keep searching for new opportunities while employed as in Pissarides (1994), and quit their current job if they receive a sufficiently attractive offer. In this case, higher wages would increase the probability of staying in the current job and could thus be used to attract and motivate more productive employees. Moreover, both firms and workers can decide to interrupt a match and might not do so randomly. Either or both sides of the market may learn about productivity over time as in Postel-Vinay and Robin (2002), or characteristics of the worker may be observable but not contractible as in Peters (2010). In all of these cases there are self-selection processes at work, and thus do not entail the randomisation described above. As a consequence, wages, industry experience and firm tenure may be affected by a common set of unobservables. The empirical model below takes this into account.

Let $i = \{1, ..., N\}$ identify a worker, and $t = \{1, ..., T\}$ a time period. Let $J(i,t)$ be the firm worker i is employed by, in period t. In the following, $J(i,t) \equiv j$ is used for simplicity. Equivalently $K(J(i,t))$ denotes the sector of worker i in period t, and $K(J(i,t)) \equiv k$.

A useful starting point for illustrative purposes is a linear wage model such as:

$$w_{ijt} = \gamma_1(seniority_{ijt}) + \gamma_2(sectorseniority_{ikt}) + \gamma_3(experience_{it}) + \epsilon_{ijt} \tag{1}$$

where w_{ijt} is the real wage of worker i working in job j in period t. $seniority_{ijt}$ is the duration of the match j up to period t, $sectorseniority_{ikt}$ is the experience accumulated by worker i in sector k up to period t, and $experience_{it}$ is the total labour market experience of worker i up to time t.

The error term ϵ_{ijt} can be decomposed into θ_i, i.e. an unobserved component that does not change for a worker across her career (e.g. unobserved ability), a match effect δ_{ij} and a component that is match-, time- and person-specific ν_{ijt}:

$$\epsilon_{ijt} = \theta_i + \delta_{ij} + \nu_{ijt} \tag{2}$$

An OLS procedure yields unbiased estimates of γ_1, γ_2 and γ_3 in equation (1) only if experience, industry experience and job seniority are uncorrelated with θ_i, with δ_{ij} and with ν_{ijt}. OLS estimates are biased unless workers were randomly assigned to sectors and firms, and matches were randomly destroyed.

3 Empirical model

The empirical model is composed of a wage equation, a job tenure hazard equation and an industry hazard equation.

3.1 Wage equation

The wage equation is

$$\begin{aligned} ln(w_{ijt}) = \quad & \alpha_0 + \alpha_1' \mathbf{seniority_{ijt}} + \alpha_2' \mathbf{sectorseniority_{ikt}} \\ & +(1+\theta_{1i})\alpha_3' \mathbf{experience_{it}} + \sum_{t=2}^{T} \iota_t^w year_t \\ & + \sum_{t=2}^{T} \kappa_t^w sector_t + \theta_{2i} + \delta_{ij} + \nu_{ijt} \end{aligned} \tag{3}$$

where w_{ijt} is the real wage of person i at time t.

The regressors $\mathbf{seniority_{ijt}}$, $\mathbf{sectorseniority_{ikt}}$ and $\mathbf{experience_{it}}$ are modelled as piecewise linear splines, where nodes are chosen to provide the best fit to the data.

In equation (3) θ_{1i} and θ_{2i} are random person effects with zero conditional mean. $year_t$ denotes a dummy variable for year t. I include year fixed effects so that the estimates are not driven by time trends in wages and mobility. The variable $sector_t$ is a dummy for each industry. Sector fixed effects ensure that estimates are not driven by correlation between industry experience and unobserved sector characteristics. δ_{ij} is a random match effect. The α's, ι's and κ's above are parameters to be estimated. Finally, ν_{ijt} is the person-match-time specific error term, which is assumed to have mean zero conditional on all the other regressors.

3.2 Job Duration Hazard model

Employment duration[4] is estimated using a hazard model based on Kiefer (1988). The baseline hazard duration dependence is piecewise linear (piecewise Gompertz)[5]. For person

[4] *Job duration*, *employment duration*, *tenure* and *seniority* are used interchangeably here.

[5] See Pollard and Valkovics (1992) and Lillard and Panis (2003b) for additional information on the Gompertz distribution.

i employed in job j in year t, the hazard model is

$$ln(h_{ij}(\tau)) = \quad \beta_0 + \beta_1' \mathbf{seniority_{ijt}} + \beta_2' \mathbf{experience_{it}} \\ + \sum_{t=2}^{T} \iota_t^j year_t + \sum_{t=2}^{T} \kappa_t^j sector_t + \theta_{3i} + \phi \delta_{ij} \tag{4}$$

where $ln(h_{ij}(\tau))$ is the conditional log hazard, i.e. the probability that we observe a job separation for a match of length τ at time t, conditional on that match being active[6]. I can control for time-invariant personal unobserved characteristic affecting job mobility through the person effect θ_{3i}. The random match effect δ_{ij} from equation (3) with the a load parameter ϕ accounts for potential cross-equation correlation between the job-level wage components and the job-level turnover hazard. The remaining regressors and parameters are defined as in equation (3).

3.3 Sector Duration Hazard model

For person i employed in sector k in year t, the hazard model is

$$ln(h_{ik}^s(\tau)) = \quad \gamma_0 + \gamma_1' \mathbf{sectorseniority_{ikt}} + \gamma_2' \mathbf{experience_{it}} \\ + \sum_{t=2}^{T} \iota_t^s year_t + \sum_{t=2}^{T} \kappa_t^s sector_t + \theta_{4i} \tag{5}$$

where $ln(h_{ik}^s(\tau))$ is the conditional log hazard, i.e. the probability of employment in sector k ending at time t, conditional on that sector spell not having been destroyed earlier. Equivalently as above, θ_{4i} is a person random effect. The splines $\mathbf{sectorseniority_{ikt}}$ and $\mathbf{experience_{it}}$ are specified as in equation (3). Equation (5) does not include a match random effect. This implies that I assume that match quality may affect the probability of changing jobs, but having taken this effect into account, it has no further effect on the probability

[6] In the data, I cannot distinguish quits and layoffs and so I need to treat them equivalently.

of changing sectors. This is equivalent to assuming that workers and firms are aware that match effects are transitory in nature.

3.4 Assumptions on parameters

I assume a first-order autoregressive error in equation (3):

$$\nu_{iJ(i,t)t} = \omega \cdot \nu_{iJ(i,t-1)t-1} + u_{iJ(i,t)t} \tag{6}$$

where $u_{iJ(i,t)t} \sim N(0, \sigma_u^2)$. Errors may thus be correlated within a worker's career, beyond the correlation induced by the presence of a person effect. I make an equivalent normality assumption for the match effect, such that $\delta_{ij} \sim N(0, \sigma_\delta^2)$.

Two sets of elements introduce simultaneity in the three-equation model described above. First, the individual effects are allowed to covary across equations (3), (4) and (5):

$$(\theta_{1i}, \theta_{2i}, \theta_{3i}, \theta_{4i})' \sim N(\mathbf{0}, \mathbf{\Sigma}_{\theta,\theta})$$

If industry experience and job tenure are exogenous in the wage equation there would be no cross-equation correlation between the $\theta_{\bullet i}$'s.

Secondly, a load factor ϕ is introduced in equation (4) as a coefficient of the match random effect component δ_{ij} defined in equation(3). A significant estimate for ϕ would suggest that some unobserved factor varying at the firm or at the job level affects wages and employment duration. The hypotheses on the $\theta_{\bullet i}$'s and on ϕ are tested separately and jointly using a Likelihood Ratio test.

3.5 Identification

Because the person and match effects in my simultaneous equation model are random effects, all effects of interest are identified off a mix of within person and match variation (i.e. variation that comes from observing multiple matches for each worker and multiple wage observations for each match) and between person and match variation (i.e. variation that comes from the fact that I observe multiple worker for each year and for each sector). Therefore, technically all effects would be identified off functional form even if I did not observe multiple jobs in multiple sector, and many wage observations for each worker's match.

However, the fact that in the dataset described below I do I observe multiple jobs per person, possibly in multiple sectors, and yearly wage observations for each job helps to separately identify them, so that effects are not identified off of functional form alone. I can use wage variation within a job as a source of identification of the effects of job seniority on wages, and wage variation within a person's career across sectors helps to separately identify the wage effects of industry experience and of labour-market experience. The effects of labour-market experience are in turn identified off in part using workers for whom I observe more than one employer. The discussion in Greene (2003, pages 295-298) for additional details on identification of random effect models, and Lillard (1999) for a discussion of identification of simultaneous equation models.

For equations (4) and (5) the individual component is identified in part using multiple spells for each worker before the last spell observed, which may be right-censored because the most recent match might be alive at the end of the dataset. Since workers may or may not change sector when they change jobs, I can identify all parameters in the sector hazard equation separately from those of the job tenure equation. As suggested by Lillard (1999) the variance of the person-specific heterogeneity term can be identified because we observe several match durations for each worker.

4 The Italian labour market in the 1980s-2000s

The empirical investigation in this paper uses a long panel of Italian workers. An extensive description of the institutional features of the Italian labour market is beyond the scope of this paper. Addessi and Tilli (2009), Beccarini (2009) and Schindler (2009) offer a more comprehensive analysis.

After a long period of stagnation of both employment and wages in the 1980s, in the 1990s Italy experienced an increase in labour force participation and and a fall in the unemployment rate. This can be traced back to the consistent growth of temporary and part-time employment, especially for young workers. Increased flexibility has been introduced "at the margin" through a series of reforms that affected primarily new entrants in the labour force (Schindler 2009). The empirical analysis below is based on a younger-than-average segment of the working population, who face a labour market that is more flexible in terms of wages and job security, and where short-term contracts are common.

5 Data

5.1 The *WHIP* Dataset

The empirical work is based on the *Work Histories Italian Panel* (WHIP). WHIP is a database of individual work histories for the years 1985-2004, based on administrative archives from the *Istituto Nazionale della Previdenza Sociale*[7] (INPS), which is the main institution for social security in Italy[8]. By law, all employees in the private sector, some categories of employees of the public sector and most self employed are enrolled in INPS,

[7]National Institute for Social Security.

[8]WHIP is managed by Laboratorio Revelli Centre for Employment Studies - that has been constructed thanks to an agreement between the INPS and the University of Torino. See http://www.laboratoriorevelli.it/whip. Detailed descriptions of the WHIP dataset are available from Contini (2002) and Contini and Trivellato (2005).

the exceptions being some categories of professionals, such as doctors, lawyers, notaries and journalists, who have alternative social security funds. The black market, which represents a significant share of the Italian labour market, is also absent.

The reference population of WHIP is all individuals that have worked in Italy in any of the years of the panel. From this population, the WHIP sample is constructed using four birth dates for each year, so that the sampling ratio is around 1:90. This results in a dynamic population of about 370,000 people. WHIP includes information about the main episodes of the working careers of people in the sample, such as dates of match creation and match destruction for each employment spell, wage received, non-working spells, other benefits received by the employee such as unemployment and mobility benefits, special arrangements, occupation, location. Individual data also include gender, year and region of birth, amount of unemployment compensations, maternity leave compensation and other social assistance programs[9]. All jobs are identified by a unique job identifier[10]. This paper uses employees of the private sector only, for which the database also provides some information about employers such as firm size, region, sector[11] where each worker is employed.

5.2 Sample selection

Industry experience, labour market experience and job tenure are left-censored for all individuals in WHIP because no information is available on employment spells before 1985. I restrict the sample to individuals for whom this left-censoring is not an issue, by selecting a sample of young workers: I drop all individuals that are employed in the first year of the panel, 1985, and then I restrict the sample to individuals that are born in 1961 or later (i.e. that are under 26 years of age in 1986). All of the results below are based on a population of

[9]And do not include educational attainments.

[10]For legal reasons firm identifiers are not included in the dataset, and thus it is not possible to identify workers that share the same employer.

[11]The classification used for this version of the dataset includes 34 sectors and it is based upon the one digit Ateco91 system.

workers that are on average younger than the overall Italian labour force: the oldest worker in the regression sample is 25 years of age is 1986, and thus is 43 years of age in 2004, the last year of the panel.

The final sample consists of 82,114 male workers and 56,914 female workers. The total number of job spells is 207,501 for males (of which 20.5 percent are right-censored) and 134,941 for females (of which 21.1 percent are right-censored). It includes 536,277 yearly wage observations for male workers, and 358,591 for female workers. Wage measures are converted into year-2004 Euros by using aggregate CPI data from Istat (2009)[12]. To make jobs of different lengths comparables in terms of wages, I construct annual *Full Time Equivalent* wages for all workers. I divide total wages by the number of days worked and the multiplying by 312, the total number of days of full time workers.

As mentioned above, WHIP includes information about start date and end date of each job but wages are recorded only once a year. I identify a a *dominant* job for every worker and every year[13] to avoid overweighting observations for short employment spells and to avoid imputing wages within a year. Therefore, the dataset I use for all regressions has one observation for each worker for each year.

6 Summary Statistics

In my sample, 61 percent of the workers are male and 39 percent are female. Around 90 percent of the workers are in a full-time job. Table 1 shows the distribution of workers by sector. For males, *Construction* is the largest sector (18.2 percent of workers), followed by *Wholesale and Retail Trade* (13.8 percent) and by *Banking and financial intermediaries* (10 percent). Females are most likely to be employed in the *Wholesale and Retail Trade* sector

[12] *Istituto Nazionale di Statistica.*

[13] I eliminate all jobs with less than five *full-time equivalent* working days, then I rank jobs by number of effective full-time-equivalent days and then by duration and wages.

(19.9 percent), and in the *Banking* sector (16.0 percent)[14].

Given that the empirical strategy relies on identifying person and job random effects through mobility, it is crucial to investigate how much mobility is observed in the data. Table 2 shows that there is a relatively large degree of mobility: we observe one employment spell for 37.6 percent of male workers in the sample, two spells for 24.3 percent, three spells for 15.4 percent of the sample. Female workers are slightly less mobile than male workers in our data. Figure 3 shows that we observe around 44 percent of males in more than one sector, and around 17 percent in at least three sectors. The corresponding figure for females are only slightly smaller.

Table 4 shows that employment spells of males last on average just over two years. In the sample used here, around 20 percent of the spells are right-censored. Male workers enter employment spells with around 20 months of experience on average, and with around 8 months of experience in the sector. Equivalent figures for female workers are presented in table 5. In this sample, females stay on the job slightly longer than males, and enter an employment spell with slightly less experience in the labour market and in the sector.

As shown in Tables 6 and 7, male workers in this sample earn on average around 19,700 Euros and females around 17,900 Euros, calculated on a full-time full-year equivalent using real wages in 2004 Euros. At the start of the year, male (female) workers have on average 3.66 years (3.56 years) of experience in the labour market, 2.72 years (2.72 years for females) of experience in the sector, and have accumulated tenure on the job of 2.02 years (2.02 years for females). The firm size is on average around 1,600 employees for males and 1,200 employees for males. Looking at the mean alone is misleading: around 45 percent of workers are employed in a firm that has less than 10 employees, only 15 percent of workers are employed by firms that have more than 300 employees.

[14]Table 1 is based on workers' first job only. This is done for clarity, and these distributions are not sensitive to this choice.

6.1 Wage Profiles

Figure 1 shows that there is a strong positive correlation between experience and log wages. The difference in wages between males and females is large and increases with the level of experience for the first ten years. At the beginning of their careers, males and females have similar wage levels, but at around ten years of experience males earn around 20 percent more than females. Women with 15 years of experience have average wages that are similar to those of men with around half as much labour market experience.

Figure 2 presents the unconditional correlation between log wages and experience accumulated in the same industry. The pattern is similar to figure 1, although the gap between males and females is even larger here and increasing for all levels of industry experience. Figure 3 shows the equivalent log wage profile for match duration. In this case all of the gap between males and females is accumulated in the first few years of job tenure.

6.2 Hazard kernel estimates

Dropping right-censored spells, the median duration of a job is 6.42 years for males and 6.50 for females; the 25th percentile of survival time is 3.17 years for males, 3.08 for females; the 75th percentile is 11.67 years for males, 12.08 for females.

The survivorship function for employment spells (Figure 4) shows that the survival probability of jobs declines roughly linearly with spell duration. At five years of job tenure, about half the matches have been destroyed. Around one fourth of the matches observed in the regression sample last more than twelve years. A kernel density estimation[15] of the hazard rate constructed in Figure 5 reveals that the hazard rate is fairly stable for the first 10 years of an employment spell, and it increases thereafter.

Median tenure in a sector is 8.56 for both males and females. The 25th percentile is

[15] All of these kernel estimations use the Epanechnikov kernel.

3.91 for males, 3.77 for females; the 75th percentiles is 14.46 for males, 14.54 for females. The estimates of the survivorship function and of the hazard rate for industry experience (Figures 6 and 7) are similar to the job tenure hazard function.

7 Regression Results

Estimates of equations (3), (4) and (5) are presented in three separate tables for male and female workers[16]. Column "SIM" refers to the most general specification: the three- equation simultaneous model where individual and match effects are allowed to be correlated across equations. Therefore, for column SIM all three tables refer to a single estimation. Unless mentioned otherwise, all coefficients described below are statistically significant at the 1 percent level.

7.1 Males

Table 8 presents the estimates of different specifications based upon equation (3) for male workers. In the column SIM, the first two years of industry experience are associated with an average wage increase of 2.1 percent per year. The years between the second and the fifth are associated with slightly negative marginal effect on wages: while some industry experience has positive returns, workers with an intermediate level of industry experience are not paid more than workers with less industry experience. It is possible that while highly mobile workers might be driven by choice and high motivation, intermediate levels of industry experience might signal a previous layoff. The average marginal effect of industry experience on wages is small, positive and stable after the fifth year at 0.7 percent a year.

Controlling for industry experience, job tenure has a very small effect on wages: the first two years are associated with an average wage increase of 0.5 percent per year; the

[16]This 3-equation model is estimated using aML (Applied Maximum Likelihood), a software developed by late Lee A. Lillard and Constantijn W.A. Panis (Lillard and Panis 2003a).

equivalent effect falls to 0.3 percent per year in the following three years, and it is not significantly different from zero for the years 5th-10th. After the tenth year on the job, the effect is slightly negative, and significant at the 5 percent level, suggesting that staying on the same job for very long may be detrimental for wages. The effect of labour market experience on wages are large and stable across our three specifications. The marginal yearly effect for the SIM specification is 4.3 percent for the first five years and around 1.5 percent afterwards. Assuming wages reflect productivity and thus human capital, these results suggest that general human capital and sector-specific human capital are both more important that firm-specific human capital. It is of interest to note that the effects of experience are large even after many years in the labour market. Trade unions, which in Italy typically include workers across many sectors, might affect returns to experience more than returns to job or industry tenure.

Table 9 presents the results for the hazard regression for spell duration. The first two years of job seniority are associated with a lower probability of match destruction. However, the estimates are much closer to zero once individual heterogeneity and simultaneity are introduced, falling from around 32 percent in model J1 to around 5 percent in SIM. The average worker that is in a longer lasting jobs differs systematically from the average worker that has shorter employment spells. Focusing on the SIM column, seniority has a negative impact on the probability of match destruction; the marginal effect is strongest for the years second to fifth. It is informative to interpret these estimates within the context of a framework where where it might take time for employers and employees learn about match-specific productivity as in Jovanovic (1979) and Jovanovic (1984). The longer a match survives the more likely it is that it survives further. In addition, each year between the second and the fifth has a large effect: which suggests there may be substantial learning in that range of spell duration.

Estimates for the effect of labour market experience on the employment hazard rate for SIM show that each of the first five years in a worker's career is associated with a 4.4 percentage-point lower log hazard rate. The following five years on the other hand are associated with a rise in the exit rate. Workers have the highest probability of leaving their job very early in their careers or after their first five years. While the former might be driven by lower-quality matches for inexperienced workers, the latter may be related to the fact that workers with more than five years of experience are in a better bargaining position with a new employer. Their better outside option might in turn increase their exit rates.

The estimates for equation (5) for male workers are outlined in Table 10. In SIM, the effect of industry experience on the conditional probability of leaving a sector is negative and large for the first two years and positive and smaller afterwards. Workers are most likely to leave an industry at the very beginning or after many years of employment in it, conditional on all other covariates. A possible interpretation of these estimates parallels that of the job hazard model above: if it takes time for the agents involved to learn the relevant productivity parameters, then lower levels of industry experience are associated with a lower exit probability, while as industry experience gets higher it is associated with a higher exit probability, even higher than the initial exit rate after around eight years of sector tenure. Similar patterns can be observed for labour market experience: ceteris paribus, more labour-market experience increases the conditional probability of leaving a certain sector. Workers with the same experience in one sector but more labour market experience are more mobile. This is not surprising given that opportunities in other sectors might increase with labour-market experience.

Tables 11 presents the estimates for the variances (the σ's) and covariances (the ρ's) of the heterogeneity components and of the error structure. In the SIM column, σ_{θ_1} is significantly different from zero, showing that there are unobservable characteristics of male workers that affect the wage returns to labour market experience[17]. The parameter σ_{θ_2} is

[17] One obvious example is educational attainments.

also significant and shows that there are individual unobservables that matter for wages above and beyond heterogeneity in returns to labour market experience. σ_{θ_3} and σ_{θ_4} are also significantly different from zero: individual unobservables affect match duration and the accumulation of industry experience. These results are also reported by Abowd, Kramarz, and Margolis (1999), Lillard (1999) and Dostie (2005).

More interestingly, all correlation coefficients ρ between individual heterogeneity variance components are significantly different from zero: I can reject the null hypothesis of no simultaneity across the three equations at all conventional significance levels. The correlation coefficient between the person random effect in the job hazard model and in the wage equation $\rho_{\theta_2\theta_3}$ is negative and significant, which implies that on average individuals with conditionally higher wages also have a lower conditional probability of job destruction. These results are consistent with the implication of a search model a la Mortensen and Wright (2002) where matches that last longer are of higher quality in terms of productivity. The estimate for $\rho_{\theta_2\theta_4}$ shows that the equivalent is true also for industry experience: workers are more likely to leave a sector when they have lower conditional wages.

Looking at the match heterogeneity variance component, the negative and significant estimate for ϕ imply that there are "good" matches[18] with higher wages (conditional on all observables) and lower average conditional probability of destruction, i.e. that last on average longer. Job duration cannot be taken as exogenous in the wage equation: longer-lasting matches are not a random sample of all matches, and this is due in part to unobservables. This result is in support of the results in Dostie (2005), Abowd, Kramarz, and Margolis (1999) and Lillard (1999). Quantitatively, a job that has a match effect that is one standard deviation higher than zero in the wage equation, equivalent to a wage gap from average of around 4,600 Euros of year 2004, has a predicted probability of destruction that is around

[18] As in Lillard (1999) and Dostie (2005) the match effect includes both a firm effect and a *pure* match effect.

9.5 percentage points lower[19].

The hypotheses of exogeneity of job and industry experience in the wage equation can also be tested jointly using a Likelihood Ratio test that compares the likelihood function of the restricted model based on the implicit assumption of no simultaneity (column "W2+J2+S2") against the unrestricted model (column SIM). This test rejects the null hypothesis of no simultaneity at any conventional significance level.

7.2 Females

In order not to make this section excessively tedious, the focus here is specifically on the aspects of the estimates in which males and females show different patterns. There are two reasons for having estimated this model for females and males separately. Firstly, it is of direct interest to look at the estimates for males and females separately because of the overall differences between labour-market performances and dynamics for the two genders. Secondly, possible dynamic selection effects might reduce the generality of results for females. This concern may be especially relevant in the Italian context where females have among the lowest participation rates in the OECD. Females with lower than average returns to experience or tenure may be more likely to leave the labour force and thus the sample, and thus estimates may represent the returns for those who decide to stay can be viewed as an upper bound.

Table 12 presents the estimates of equation (3) for female workers. The estimates of the SIM model show that the first two years of industry experience are associated with an average wage effect on 2.5 percent a year. The years between the second and the fifth are associated with slightly negative marginal effect on wages, and the effect is stable thereafter at 0.5 percent. This is largely in line with results for males. Wage returns for the first 2 years of job seniority are higher than males' at 1.2 percent; they fall to a negative 0.3 percent for

[19] Calculated as $(-0.455) \times (0.209)$.

years 3-5, and levels off at positive 0.4 percent a year after more than ten years. The wage returns of labour market experience are much lower for females than for males. Focusing on the results of the SIM model, the first five years show an average yearly effect of 1.6 percent and at 0.6 percent afterwards. This is consistent with the unconditional experience wage profile shown in figure 1 where the gap between males and females is growing in the number of years of labour market experience. Sectors and jobs that are more common for males value previous labour market experience more than those that are dominated by females'. Further research is required to investigate this finding and identify the specific channels and the reasons for which females' wages are much less affected by labour-market experience when compared to males'.

Tables 13 presents the results for the hazard model of employment duration for females. Estimates are qualitatively very similar to those for males. Despite the absence of any strong pattern, coefficients for females tend to be smaller. These differences could be due to events affecting mobility and labour market participation of females, such as maternity, health problems in the family, elderly care etc. The estimates for equation (5) for females are in Table 14. The marginal effects of industry experience on the probability of changing sectors is qualitatively similar to the estimates for males, and the smaller coefficients for females are similar to those discussed above for the case of job tenure. Having between five and ten years of experience increases the hazard rate more for females than for males. This is not surprising since the effect of labour market experience on wages is significantly smaller for females.

Equivalent to males, individual heterogeneity components are large for female workers, as shown in Table 15, suggesting that individual unobservables are important for wages, sector and job mobility of females as well. All correlation coefficients between individual random effects are significantly different from zero. This finding provides further evidence against the null hypothesis of no simultaneity across equations. Two coefficients have the opposite sign in comparison to the estimates for males. $\rho_{\theta_1\theta_3}$ and $\rho_{\theta_1\theta_4}$ are both positive for females while they are negative for males. Female workers with higher conditional returns to experience also have higher probability of leaving the job and the industry they are employed in. Overall, female workers have low returns to experience compared to males. The females that have higher returns to experience seem to be more similar to males in terms of mobility patterns, in that they have higher job and sector mobility than other females.

The estimate for the match heterogeneity component ϕ is negative and significant as it is the case for males. The estimated coefficient implies that a job that has a match effect one standard deviation higher than zero in the wage equation, equivalent to a gap from the average of around 3,600 Euros of year 2004, has a predicted probability of destruction that is around 7.2 percentage points lower[20]. The Likelihood Ratio Test rejects the null hypothesis of no simultaneity at any conventional significance level.

I have run some additional specifications for males and females. Including firm size in the wage regression shows that, consistent with previous literature (see e.g. Troske 1999 for evidence using matched data), larger firms pay higher wages ceteris paribus. However, its inclusion does not have any sizeable effect on the other estimates. As discussed earlier, the inclusion of occupation controls changes the estimates very marginally.

8 Concluding Remarks

In this paper I use panel data for a sample of Italian workers in years 1986-2004 to estimate the effect of industry experience on wages taking account of heterogeneity at the individual and match level to affect mobility and wages and also allow to tests for the presence of this simultaneity. The main results show that industry experience has a much stronger impact on wage dynamics than job tenure. Estimates show that wage returns to job seniority are

[20] $(-0.394) \times (0.183)$.

very small, and that the returns to labour market experience and industry experience are highly nonlinear, concentrated in the first years and very small afterwards. There is also clear evidence of the endogeneity of job seniority and industry experience in the wage equation coming from the effects of unobserved individual and match unobserved heterogeneity.

The Italian labour market, which is considered among the most rigid in the OECD countries[21], job search and job match considerations are found to be important determinants of wages of workers in the early part of their careers. These results imply that earning losses from a layoff depend on the opportunity that the worker has within the same sector, because mobility across labour-market sectors is associated with a higher short-term wage penalty than mobility within the same sector. Labour market policies might consider specific interventions for displaced workers employed in a shrinking sector as opposed to displaced workers in a booming sector.

This paper has an empirical focus and is largely silent about the mechanism through which labour-market experience, experience within one industry and job seniority affect wages. Assuming experience and seniority affect wages through human capital accumulation, my results suggest that industry-specific human capital is more important than firm-specific human capital. There are a number of competing explanations, and future research is needed to discriminate among some of these explanations. Estimates may at least in part be driven by the role of labour market networks: industry experience might matter for wages through its possible effect on a worker's outside option, which may depend on a worker's network. Within the Italian context it would also be important to investigate the role of trade unions, which are in some cases sector-specific, but for the most part operate across sectors in Italy. Future research should also move beyond estimations of average effects and investigate the distribution of returns to industry experience across sectors, occupations, regions, and across the wage distribution.

[21] See for example Contini and Trivellato (2005).

APPENDICES

A Summary statistics

Table 1: Economic sector of the firm

	Distribution of workers	
Economic sector	Males	Females
Farming and hunting	0.2	0.1
Fishing and fish farming	0.1	0.0
Extraction of energy material	0.0	0.0
Extraction of non-energy material	0.3	0.0
Food, beverages and Tobacco	3.5	4.0
Textile and clothing	2.3	8.5
Leather and fur	1.3	2.0
Wood Industries	1.8	0.5
Paper and press	1.6	1.3
Oil refineries	0.1	0.0
Chemicals and related industries	1.2	1.0
Rubber and plastic industries	1.7	1.2
Products for working non-metal minerals	1.9	0.9
Production of metals and metal products	9.5	3.2
Production of machineries	3.4	1.3
Production of electrical and optical machinery	4.6	3.5
Production of means of transportation	1.3	0.5
Other manufacturing	2.7	2.1
Production and distribution of electrical power, water and natural gas	0.3	0.2
Construction	18.2	1.9
Wholesale and retail trade, auto reparations	13.8	19.9
Hotels and restaurants	7.9	12.1
Transport, warehouses and communications	5.2	2.4
Banking and financial intermediaries	10.0	16.0
Computing and rental services, research and other business related sectors	1.0	1.8
Public administration and defense	2.3	5.0
Education	0.6	2.7
Health	0.5	1.8
Other Public, Social and personal services	2.0	5.5
Missing values	0.4	0.4
Number of observations	82,114	56,914

Source: Calculations from WHIP dataset, calculated from each worker's first job

Table 2: Number of Jobs and Conditional Average Duration

	Males		Females	
Number of jobs	**Percentage**	**Avg Job Duration**	**Percentage**	**Avg Job Duration**
One job	37.6	2.95	40.4	2.99
Two jobs	24.3	2.60	24.6	2.64
Three jobs	15.4	2.14	15.4	2.18
Four jobs	9.5	1.80	8.9	1.83
Five jobs	5.8	1.54	5.0	1.56
More than five jobs	7.4	1.10	5.8	1.04
Total	100.0	2.01	100.0	2.10
Frequencies	82,114		56,914	

Unit of observation is the worker

Table 3: Number of Sectors

	Males	Females
Number of sectors	**Percentage**	**Percentage**
One sector	55.7	58.1
Two sectors	27.4	27.6
Three sectors	11.3	10.3
More than three sectors	5.6	4.0
Total	100.0	100.0
Frequencies	82,114	56,914

Unit of observation is the worker

Table 4: Summary statistics for Job Covariates - Males

Variable	**Mean**	**(Std. Dev.)**	**Min.**	**Max.**	**N**
Job duration (years)	2.01	(2.82)	0.08	18.92	208208
Dummy for censored job spell	0.20	(0.40)	0	1	208208
Sector spell duration	3.60	(3.89)	0.04	18.87	208208
Experience at the beginning of the job spell	1.62	(2.62)	0	17.91	208208
Experience in the sector	0.71	(1.76)	0	17.91	208208

Unit of observation is the job

Table 5: Summary statistics for Job Covariates - Females

Variable	Mean	(Std. Dev.)	Min.	Max.	N
Job duration (years)	2.10	(2.83)	0.08	18.92	135408
Dummy for censored job spell	0.21	(0.41)	0	1	135408
Sector spell duration	3.60	(3.90)	0.04	18.87	135408
Experience at the beginning of the job spell	1.56	(2.60)	0	17.78	135408
Experience in the sector	0.69	(1.77)	0	17.34	135408

Unit of observation is the job

Table 6: Summary statistics for Year-level Covariates - Males

Variable	Mean	(Std. Dev.)	Min.	Max.	N
Real wage for full year employment	19738.47	(9207.73)	107.49	199393.5	537127
Experience at the start of the year	3.66	(3.83)	0	17.91	537127
Sector tenure at the start of the year	2.72	(3.39)	0	17.91	537127
Job tenure at the start of the year	2.02	(3.00)	0	17.91	537127
Average employees of the firm	1672.75	(9595.56)	0	114514	430472

Unit of observation is the worker-year

Table 7: Summary statistics for Year-level Covariates - Females

Variable	Mean	(Std. Dev.)	Min.	Max.	N
Real wage for full year employment	17859.53	(7454.51)	101.13	198854.67	359186
Experience at the start of the year	3.56	(3.74)	0	17.91	359186
Sector tenure at the start of the year	2.72	(3.37)	0	17.91	359186
Job tenure at the start of the year	2.02	(2.93)	0	17.91	359186
Average employees of the firm	1211.68	(6994.83)	0	113918	288675

Unit of observation is the worker-year

Figure 1: Experience Profile based on annual data

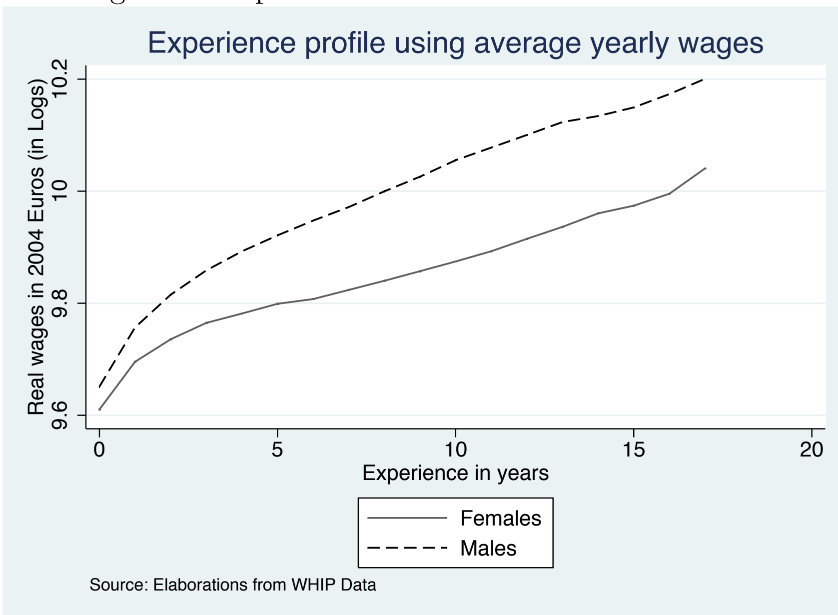


Figure 2: Industry Experience Profile based on annual data

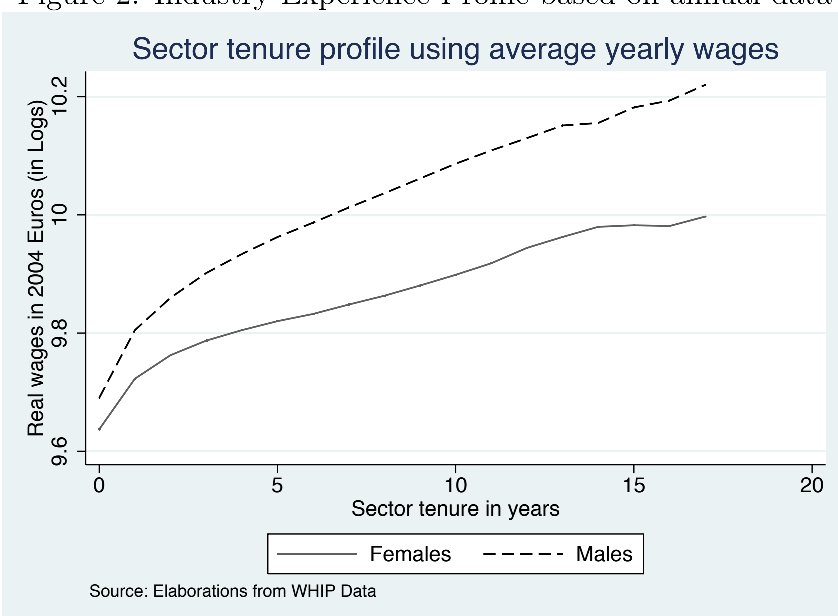


Figure 3: Job Tenure Profile based on annual data

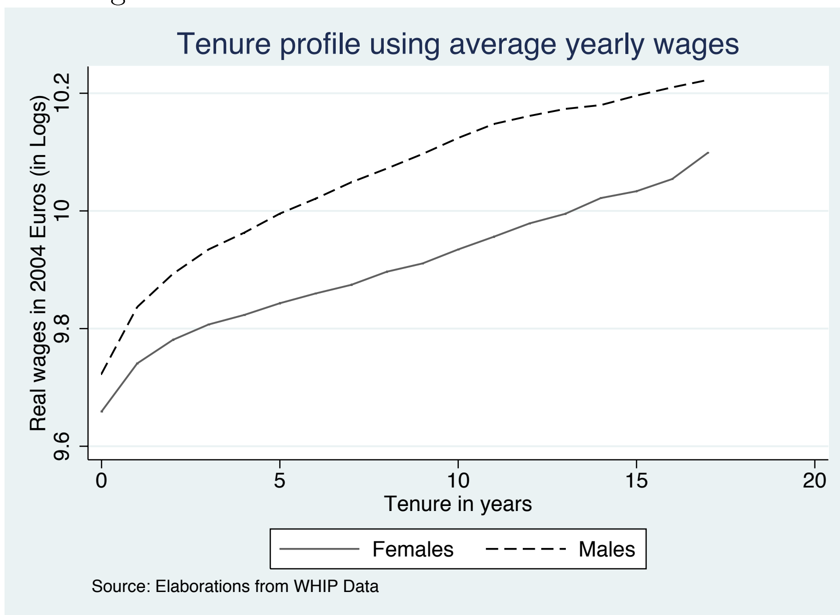


Figure 4: Survivorship Function for Job Tenure

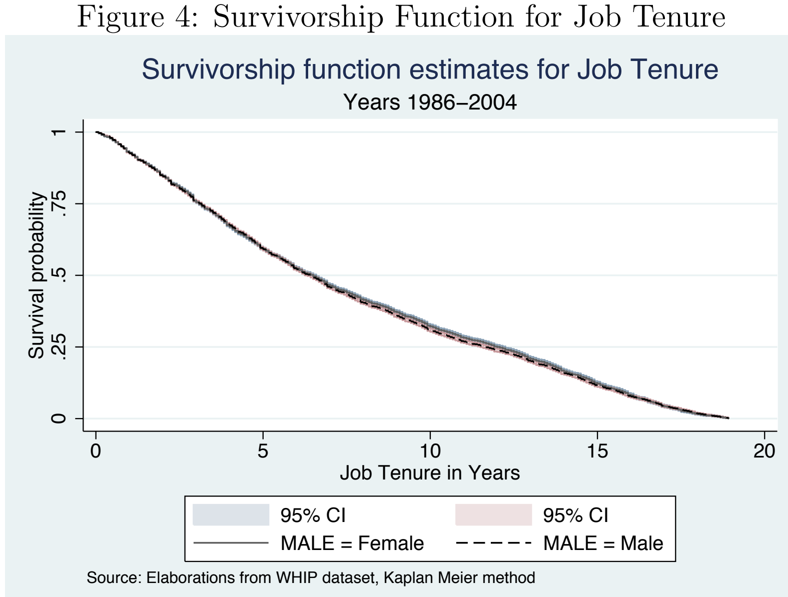


Figure 5: Hazard Function for Job Tenure

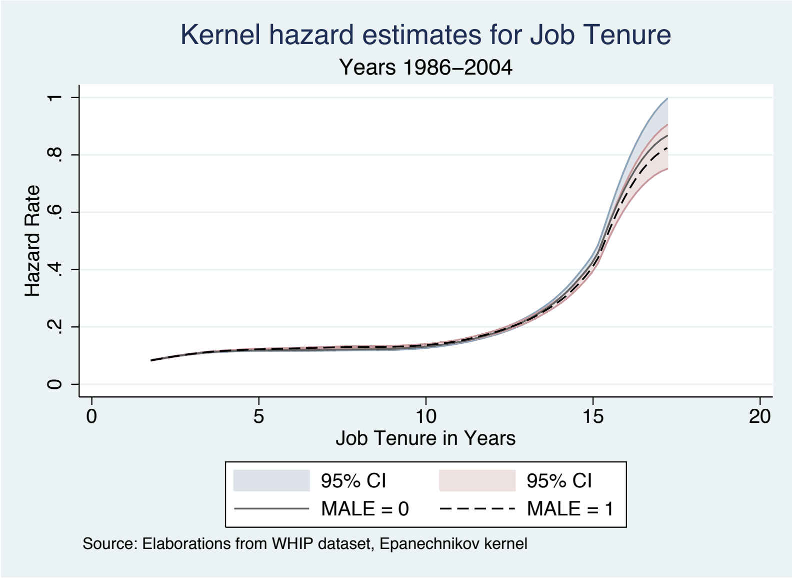


Figure 6: Hazard Function for Sector Tenure

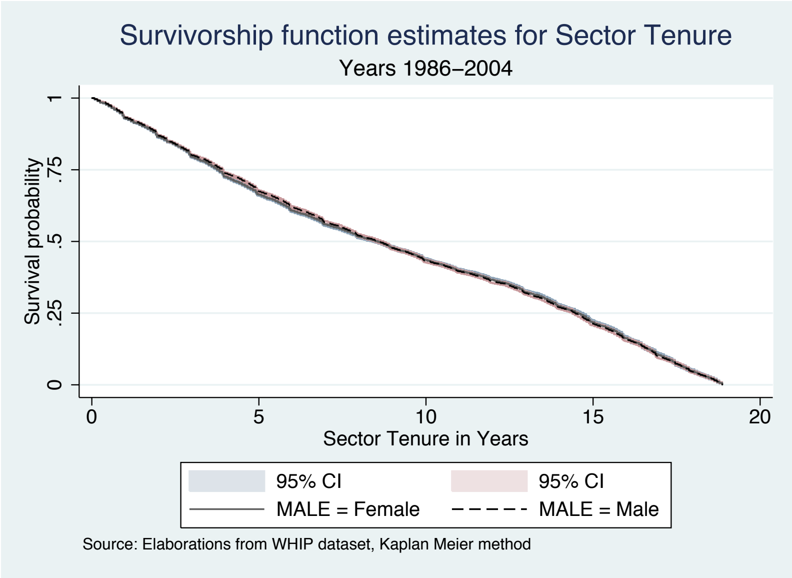
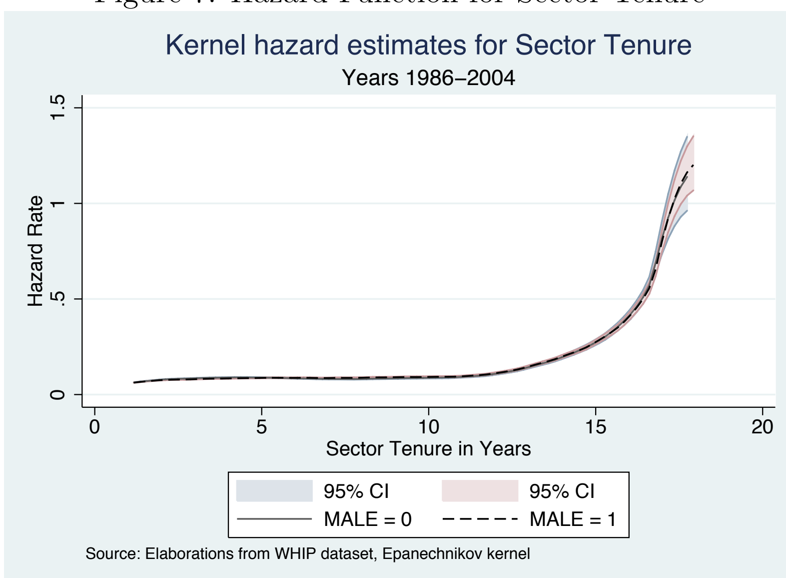


Figure 7: Hazard Function for Sector Tenure



B Regression Tables

Table 8: Wage Equation for Males

Dependent variable: $ln(w_{iJ(i,t)t})$

Variables	Models		
	W1	W2	SIM
Constant	9.700***	9.628***	9.603***
	(0.016)	(0.017)	(0.017)
Industry Experience			
0-2nd year	0.034***	0.024***	0.021***
	(0.001)	(0.001)	(0.001)
3rd-5th year	0.003***	-0.005***	-0.003***
	(0.001)	(0.001)	(0.001)
6th-10th year	0.004***	0.005***	0.007***
	(0.001)	(0.001)	(0.001)
11th year +	0.004*	0.004***	0.007***
	(0.002)	(0.001)	(0.001)
Job Seniority			
0-2nd year	0.004***	0.004***	0.005***
	(0.001)	(0.001)	(0.001)
3rd-5th year	0.007***	0.002*	0.003***
	(0.001)	(0.001)	(0.001)
6th-10th year	0.007***	0.000	0.001
	(0.001)	(0.001)	(0.001)
11th year +	0.000	-0.003**	-0.003**
	(0.002)	(0.001)	(0.001)
Experience			
0-5th year	0.034***	0.042***	0.043***
	(0.001)	(0.001)	(0.001)
6th-10th year	0.017***	0.015***	0.015***
	(0.001)	(0.000)	(0.000)
11th year +	0.015***	0.014***	0.014***
	(0.001)	(0.000)	(0.000)

Number of yearly wage observations: 536,277

Time and sector fixed effects in all regressions

W1: Wage model without Unobserved Heterogeneity components

W2: Wage model with Unobserved Heterogeneity components

SIM: 3-Equation Simultaneous model

Asymptotic Standard Errors in Parenthesis

Significance: *=10%; **=5%; ***=1%

Table 9: Job Hazard Equation for Males

Dependent variable: $ln(h_{iJ(i,t)t}(\tau))$

Variables	Models		
	J1	J2	SIM
Constant	0.06	0.000	0.398***
	(0.043)	(0.052)	(0.062)
Job Seniority			
0-2nd year	-0.317***	-0.140***	-0.051***
	(0.005)	(0.005)	(0.006)
3rd-5th year	-0.114***	-0.078***	-0.140***
	(0.005)	(0.005)	(0.005)
6th-10th year	-0.069***	-0.054***	-0.072***
	(0.006)	(0.006)	(0.007)
11th year +	-0.011	-0.004	-0.007
	(0.012)	(0.012)	(0.013)
Experience			
0-5th year	-0.141***	-0.170***	-0.044***
	(0.002)	(0.002)	(0.003)
6th-10th year	-0.018***	-0.003	0.059***
	(0.003)	(0.003)	(0.004)
11th year +	-0.066***	-0.061***	-0.007
	(0.006)	(0.006)	(0.007)

Number of job observations: 207,501

Time and sector fixed effects in all regressions

J1: Job Hazard model without Unobserved Heterogeneity components

J2: Job Hazard model with Unobserved Heterogeneity components

SIM: 3-Equation Simultaneous model

Asymptotic Standard Errors in Parenthesis

Significance: *=10%; **=5%; ***=1%

Table 10: Sector Hazard Equation for Males

Dependent variable: $ln(h^s_{ik}(\tau))$			
Variables	Models		
	S1	S2	SIM
Constant	-0.414***	-0.360***	-0.015
	(0.042)	(0.055)	(0.072)
Industry Experience			
0-2nd year	-0.421***	-0.260***	-0.152***
	(0.005)	(0.005)	(0.006)
3rd-5th year	-0.028***	0.054***	0.008*
	(0.004)	(0.004)	(0.004)
6th-10th year	-0.002	0.067***	0.061***
	(0.003)	(0.004)	(0.005)
11th year +	0.002	0.079***	0.096***
	(0.005)	(0.006)	(0.007)
Experience			
0-5th year	-0.092***	-0.092***	0.036***
	(0.003)	(0.003)	(0.004)
6th-10th year	-0.022***	-0.017***	0.056***
	(0.003)	(0.004)	(0.004)
11th year +	-0.006	-0.037***	-0.008
	(0.005)	(0.005)	(0.007)
Number of job observations: 207,501			

Time and sector fixed effects in all regressions

S1: Sector Hazard model without Unobserved Heterogeneity components

S2: Sector Hazard model with Unobserved Heterogeneity components

SIM: 3-Equation Simultaneous model

Asymptotic Standard Errors in Parenthesis

Significance: *=10%; **=5%; ***=1%

Table 11: Variance components and Parameters for Males

	Models		
	W1+J1+S1	W2+J2+S2	SIM
Individual Heterogeneity variance components			
σ_{θ_1}		1.013***	1.023***
		(0.014)	(0.014)
σ_{θ_2}		0.221***	0.222***
		(0.001)	(0.001)
σ_{θ_3}		0.500***	0.898***
		(0.005)	(0.005)
σ_{θ_4}		0.719***	1.283***
		(0.005)	(0.007)
$\rho_{\theta_1\theta_2}$		-0.402***	-0.408***
		(0.005)	(0.005)
$\rho_{\theta_1\theta_3}$			0.158***
			(0.006)
$\rho_{\theta_2\theta_3}$			-0.114***
			(0.005)
$\rho_{\theta_1\theta_4}$			0.205***
			(0.005)
$\rho_{\theta_2\theta_4}$			-0.194***
			(0.004)
$\rho_{\theta_3\theta_4}$			0.947***
			(0.001)
Match Heterogeneity variance components			
σ_δ		0.209***	0.209***
		(0.000)	(0.000)
ϕ			-0.455***
			(0.017)
Error structure			
ω	0.881***	0.409***	0.407***
	(0.000)	(0.001)	(0.001)
σ_ν	0.161***	0.140***	0.139***
	(0.000)	(0.000)	(0.000)
ln-L	-1423933.75	-1397664.25	-1368727.7

Asymptotic Standard Errors in Parenthesis

Significance: *=10%; **=5%; ***=1%

Table 12: Wage Equation for Females

Dependent variable: $ln(w_{iJ(i,t)t})$			
Variables	Models		
	W1	W2	SIM
Constant	9.618***	9.579***	9.570***
	(0.018)	(0.019)	(0.019)
Industry Experience			
0-2nd year	0.032***	0.027***	0.025***
	(0.002)	(0.001)	(0.001)
2nd-5th year	0.000	-0.003***	-0.005***
	(0.001)	(0.001)	(0.001)
5th-10th year	0.006***	0.002**	-0.004***
	(0.001)	(0.001)	(0.001)
10th year +	0.000	0.000	-0.005***
	(0.003)	(0.002)	(0.002)
Job Seniority			
0-2nd year	0.014***	0.013***	0.012***
	(0.001)	(0.001)	(0.001)
3rd-5th year	0.006***	-0.001	-0.003***
	(0.001)	(0.001)	(0.001)
6th-10th year	0.006***	0.001	0.002
	(0.002)	(0.001)	(0.001)
11th year +	0.007***	0.004*	0.004*
	(0.003)	(0.002)	(0.002)
Experience			
0-5th year	0.020***	0.025***	0.016***
	(0.001)	(0.001)	(0.001)
6th-10th year	0.004***	0.008***	0.006***
	(0.001)	(0.000)	(0.000)
11th year +	0.011***	0.010***	0.006***
	(0.002)	(0.001)	(0.000)
Number of yearly wage observations: 358,591			

Time and sector fixed effects in all regressions

W1: Wage model without Unobserved Heterogeneity components

W2: Wage model with Unobserved Heterogeneity components

SIM: 3-Equation Simultaneous model

Asymptotic Standard Errors in Parenthesis

Significance: *=10%; **=5%; ***=1%

Table 13: Job Hazard Equation for Females

Dependent variable: $ln(h_{iJ(i,t)t}(\tau))$

Variables	Models		
	J1	J2	SIM
Constant	-0.200***	-0.305***	-0.041
	(0.066)	(0.074)	(0.135)
Job Seniority			
0-2nd year	-0.311***	-0.143***	-0.059***
	(0.006)	(0.007)	(0.007)
3rd-5th year	-0.072***	-0.031***	-0.088***
	(0.006)	(0.006)	(0.006)
6th-10th year	-0.050***	-0.034***	-0.060***
	(0.007)	(0.007)	(0.008)
11th year +	0.014	0.026*	0.016
	(0.013)	(0.014)	(0.015)
Experience			
0-5th year	-0.136***	-0.165***	-0.034***
	(0.003)	(0.003)	(0.004)
6th-10th year	-0.010***	0.004	0.073***
	(0.004)	(0.004)	(0.005)
11th year +	-0.055***	-0.051***	0.01
	(0.008)	(0.008)	(0.009)

Number of job observations: 134,941

Time and sector fixed effects in all regressions

J1: Job Hazard model without Unobserved Heterogeneity components

J2: Job Hazard model with Unobserved Heterogeneity components

SIM: 3-Equation Simultaneous model

Asymptotic Standard Errors in Parenthesis

Significance: *=10%; **=5%; ***=1%

Table 14: Sector Hazard Equation for Females

Dependent variable: $ln(h_{ik}^{s}(\tau))$			
Variables	Models		
	S1	S2	SIM
Constant	-0.540***	-0.587***	-0.350**
	(0.062)	(0.076)	(0.145)
Industry Experience			
0-2nd year	-0.358***	-0.207***	-0.093***
	(0.006)	(0.007)	(0.007)
3rd-5th year	-0.019***	0.061***	0.017***
	(0.004)	(0.005)	(0.005)
6th-10th year	-0.024***	0.026***	0.020***
	(0.004)	(0.005)	(0.006)
11th year +	-0.003	0.048***	0.071***
	(0.007)	(0.008)	(0.009)
Experience			
0-5th year	-0.099***	-0.105***	0.033***
	(0.004)	(0.004)	(0.005)
6th-10th year	0.004	0.013***	0.088***
	(0.004)	(0.004)	(0.005)
11th year +	0.000	-0.014*	0.017*
	(0.007)	(0.007)	(0.009)
Number of job observations: 134,941			

Time and sector fixed effects in all regressions

S1: Sector Hazard model without Unobserved Heterogeneity components

S2: Sector Hazard model with Unobserved Heterogeneity components

SIM: 3-Equation Simultaneous model

Asymptotic Standard Errors in Parenthesis

Significance: *=10%; **=5%; ***=1%

Table 15: Variance components and Parameters for Females

	Models		
	W1+J1+S1	W2+J2+S2	SIM
Individual Heterogeneity variance components			
σ_{θ_1}		1.327***	2.059***
		(0.039)	(0.086)
σ_{θ_2}		0.191***	0.193***
		(0.001)	(0.001)
σ_{θ_3}		0.496***	0.927***
		(0.006)	(0.006)
σ_{θ_4}		0.666***	1.290***
		(0.007)	(0.009)
$\rho_{\theta_1\theta_2}$		-0.373***	-0.372***
		(0.009)	(0.008)
$\rho_{\theta_1\theta_3}$			-0.294***
			(0.009)
$\rho_{\theta_2\theta_3}$			-0.058***
			(0.007)
$\rho_{\theta_1\theta_4}$			-0.252***
			(0.008)
$\rho_{\theta_2\theta_4}$			-0.125***
			(0.006)
$\rho_{\theta_3\theta_4}$			0.952***
			(0.001)
Match Heterogeneity variance components			
σ_δ		0.183***	0.183***
		(0.000)	(0.000)
ϕ			-0.394***
			(0.029)
Error structure			
ω	0.718***	0.277***	0.277***
	0	(0.002)	(0.002)
σ_ν	0.237***	0.207***	0.207***
	(0.000)	(0.000)	(0.000)
ln-L	-1010086.9	-994355.35	-975799.48

Asymptotic Standard Errors in Parenthesis

Significance: *=10%; **=5%; ***=1%

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